

Diffusion of hurricane evacuation behavior through a home-workplace social network: A spatially explicit agent-based simulation model

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ABSTRACT

With coastal populations experiencing the growing threat of hurricanes as a consequence of global climate change, models for predicting how household evacuation behavior may diffuse over time and space are needed for emergency management. This study models the effects of social influence on household evacuation behavior in anticipation of a hurricane event. An agent-based model was developed in this study to simulate: 1) a home-workplace social network between households residing in the Florida Keys, 2) the communication of a hurricane evacuation order among socially linked households, and 3) the resulting spatio-temporal diffusion of household evacuation behavior. Data sources informing model implementation include U.S. Census block group data, business databases, and statistics from hurricane evacuation surveys. Simulated model results from the model were validated with empirical traffic records observed at a Florida Keys monitoring station during evacuation from Hurricane Georges in 1998. This model builds upon previous research using agent-based models to simulate hurricane evacuation by incorporating multiple data sources and validating results with empirical traffic patterns. Such an empirically-grounded model facilitates locally relevant exploration of evacuation behavior to support the development of more effective evacuation plans and preparedness for future hurricane events.

1. Introduction

The arrival of Hurricanes Harvey, Irma, and Maria in 2017 was a stark reminder of the danger of these extreme events and their increased risk with global climate change. Meanwhile, growing populations along the Atlantic U.S. coast have become vulnerable to hurricanes, because a large number of households cannot be protected by staying in their homes or in shelters and must therefore evacuate to survive (Barrett, Ran, & Pillai, 2000; Urbina & Wolshon, 2003). In response to a hurricane evacuation order issued by local government, households must decide whether to evacuate, and their choices tend to vary over space and time (Baker, 1991; Dow & Cutter, 2000). Indeed, a household's decision-making about evacuation is not an easily predictable but rather a complex process (Gladwin, Lazo, Morrow, Peacock, & Willoughby, 2007). Modeling such a complex process for different households is thus critical to improving understanding and planning ahead for evacuation from future hurricanes and other natural disasters.

1.1. Study aim

The aim of this study is to simulate the hurricane evacuation process using a model that accounts for social influence on household decisions of whether to evacuate. In particular, this research explores the question: How might social influence affect household decisions to evacuate from a hurricane, and how do these decisions affect the resulting traffic? Taking a novel and empirically grounded approach to model development, this study contributes to research on hurricane evacuation by generating a home-workplace social network to mediate social influence, embedding this network in a spatially explicit agent-based model (ABM) to simulate the diffusion of household evacuation behavior, and using empirical data to calibrate model elements and validate simulated evacuation traffic. This model provides a virtual platform for experimentation with alternative strategies for emergency management planning.

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1.2. Background

Evacuation is a response to an emergency situation that generates distinct travel demand patterns in terms of who will evacuate and when they will depart (Pel, Bliemer, & Hoogendoorn, 2012). Evacuation decision-making is primarily determined by risk perception, as contextualized by the level of the threat, the vulnerability of the household, and the content of the message issuing a warning or evacuation order (Lindell & Perry, 2004). Evacuation behavior has been linked to a variety of factors, such as the intensity and proximity of the disaster, the structure of the traffic network, and demographic characteristics of households (Baker, 1991; Chen & Zhan, 2008; Hobeika & Jamei, 1985; Sheffi, Mahmassani, & Powell, 1982; Stern & Sinuany-Stern, 1989; Wilmot & Mei, 2004).

Studies examining demographic and socio-economic characteristics of households as determinants of evacuation behavior often assume that households make decisions independently from one another (Baker, 1991; Chen, Meaker, & Zhan, 2006; Wilmot & Mei, 2004). However, evidence suggests that social influence between households also plays an important role in affecting whether households decide to evacuate (Horney, 2009; Lindell, Lu, & Prater, 2005). Such social influence includes communication of risk (Lindell & Perry, 2004) and knowledge of others' behavior (Horney, 2009). In their review of activity-based simulation models for emergency situations, Henson and Goulias (2006) underscored the need for models that account for interactions between households and also called for simulation at finer scales of spatio-temporal resolution. By simulating social influence on evacuation in a rich spatio-temporal context, the present study thereby adds to an extensive body of research using evacuation models.

Two types of models, statistical and computational models, have been used to predict travel demand patterns associated with hurricane evacuation. Statistical models use methods such as logistic regression to understand contributing factors to evacuation decision, often based on empirical data collected through surveys. For instance, Fu and Wilmot (2004) estimated a binary logit model for Hurricane Andrew and identified statistically significant factors including: the distance to the storm, the forward speed of the hurricane, time-of-day (morning, afternoon, and night), the presence of an evacuation order, possibility of flooding, and housing type. These statistical models can then be extended from the survey sample to the entire study area to predict which households will evacuate and thereby create travel demand.

In contrast to statistical models, computational models estimate the travel demand by simulating households' decision-making process, based on established psychological and/or behavioral theories, such as risk perception, social learning, and innovation diffusion. As a class of computational models, ABMs have been increasingly used to simulate households' decision-making processes about evacuation (Chen et al., 2006; Cova & Johnson, 2002; Widener, Horner, & Metcalf, 2013; Zhang, Chan, & Ukkusuri, 2009). Cova and Johnson (2002) developed a microscopic traffic model to simulate neighborhood evacuation that could be used not only to locate bottlenecks, but also to identify which evacuees were delayed at a given bottleneck. Chen et al. (2006) estimated the clearance time for evacuees along the Florida Keys' transport network and the number of evacuees needing accommodation if the main evacuation route were not available.

An agent-based modeling approach was taken in this study to incorporate household characteristics and social interactions among households as influences on the decision to evacuate from a hurricane. This bottom-up approach to dynamic modeling allows for simulation of individuals as heterogeneous agents that interact and make decisions that affect patterns of collective behavior (Grimm & Railsback, 2005). When appropriately calibrated and validated, ABMs can provide simulated predictions under plausible scenarios to support evacuation planning (Crooks & Wise, 2013).

Some recent ABMs of evacuation have simulated social influence on evacuation in such a way that households decide to evacuate in part

because of knowledge about their friends' evacuation behavior (Madireddy, Kumara, Medeiros, & Shankar, 2015; Widener et al., 2013). These models use computer algorithms to generate abstract social networks, such as random, small-world and scale-free networks (Hasan & Ukkusuri, 2011; Madireddy et al., 2015; Widener et al., 2013). An advantage of these algorithms is that little information is required to construct the social networks. However, these abstractions can limit model utility for local evacuation planning.

This study addresses three main challenges faced by these social network ABMs (Hasan & Ukkusuri, 2011; Madireddy et al., 2015; Widener et al., 2013). First, actual social networks among households are generally unknown and thus difficult to construct accurately. Second, the model outcomes are often difficult to validate because they use abstract networks or lack reference data about evacuation dynamics. Third, geospatial location is often excluded from these models, which instead simulate diffusion dynamics among households in an abstracted topological or social space. This study addresses these challenges by developing a home-workplace social network using information on both residential and workplace locations, by validating model results with observed traffic during evacuation, and by rendering the model spatially explicit for the geographical context of the Florida Keys.

In this study, households are modeled as individual agents that make decisions about whether to evacuate after learning about an evacuation order from mass media or through their social network. These socially influenced decisions then manifest in spatial and temporal traffic patterns associated with the simulated evacuation rate. These spatio-temporal patterns are needed to infer where people are more likely to evacuate so as to coordinate evacuation traffic and avoid congestion. This simulation study contributes to previous ABM research on evacuation of populations at risk from Hurricane Georges in the Florida Keys (Chen et al., 2006; Chen & Zhan, 2008). The present study differs from this previous research in accounting for social influence among households and heterogeneity in households' evacuation tendencies.

1.3. Study area

The Florida Keys was chosen as the study area to provide a geographic context for the model that is particularly vulnerable to hurricanes (Blake, Rappaport, & Landsea, 2007). Frequently visiting hurricanes expose the population of the Florida Keys to a high risk of impact that is exacerbated by its situation as a low-lying area with access to only one arterial road for evacuation. Even as it is uniquely constrained, this linear transportation route facilitates demonstration of how to apply the model algorithms and interpret model results. The Florida Keys thus provides a relatively simple and yet relevant case study for a model that involves diffusion of evacuation behavior in a home-workplace social network. This modeling framework is capable of being extended to other vulnerable areas by accounting for other types of transportation networks and urban populations informed by GIS data.

This area is a chain of islands extending southwest from the southern tip of the Florida Peninsula (Fig. 1). More than 32% of its population is concentrated at its southernmost tip in the city of Key West (Fig. 1c), which is the farthest away from the outlet to the mainland. Since there are no shelters safe for hurricanes with Category 3 or higher, residents of the Florida Keys must evacuate to the mainland to ensure their safety (Chen et al., 2006). The United States Highway 1 (U.S.1), extending easterly 112 miles from Key West, is a single arterial road connecting islands together and with the mainland. In a hurricane event, it is the only viable evacuation route to the mainland. The single evacuation route along a linear transportation network is thus vulnerable to becoming a bottleneck of acute traffic congestion during evacuation.

A practical consideration for this study area was the availability of traffic data during hurricane evacuation that could be used for model

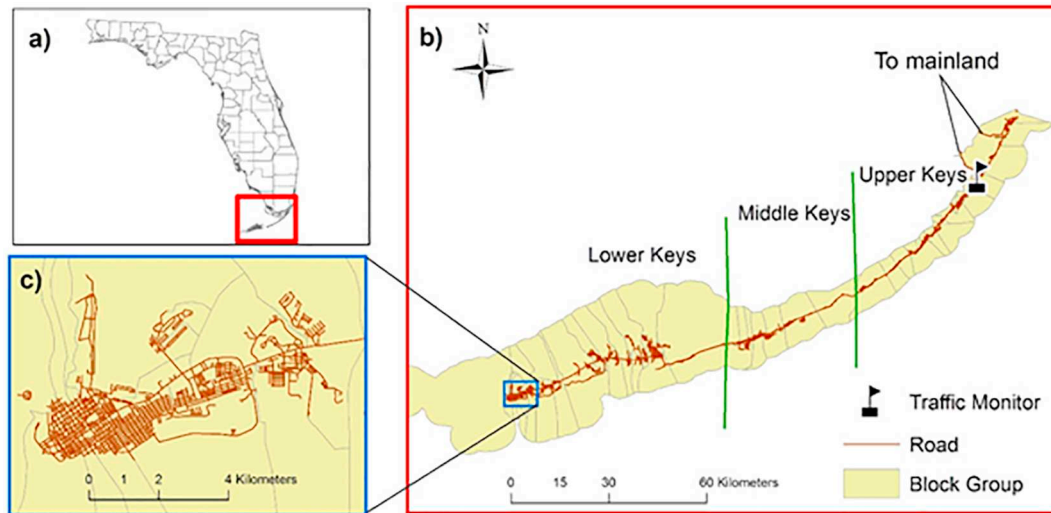


Fig. 1. These maps illustrate: a) the location of the Florida Keys in south Florida, USA; b) the extent of the Florida Keys study area; and c) the city of Key West at the southwestern tip of the study area.

validation. In this study, the simulated traffic patterns resulting from hurricane evacuation dynamics were compared with observed traffic data for evacuation from Hurricane Georges (Category 4), which hit the Florida Keys on September 25, 1998. These data were obtained from a traffic monitoring station located at the outlet of Florida Keys (Fig. 1b) that records hourly traffic between the Florida Keys and the mainland.

The following sections describe model development and implications of results from virtual experimentation with the model. Section 2 provides an overview of model design in terms of network-based diffusion dynamics. Section 3 then provides details of its implementation, including the household-level evacuation decision process and calibration of household evacuation thresholds. Results from experimentation with the model are then presented and discussed in section 4, followed by conclusions in section 5.

2. Model design

The model design consists of three interrelated components, including a social contact network among households, a diffusion process of evacuation order, and a diffusion process of evacuation behavior. After the evacuation order is issued by authorities in response to an incoming hurricane, households being informed first would discuss it with their social links, leading to communication of the hurricane evacuation order. As shown in Fig. 2, household *a* is first aware of the evacuation order and then spreads this information to social links *b*, *c*, *d*, and *e* through the social network. After being informed about the

evacuation order, each household starts to make a decision on evacuation. The decision-making process is influenced not only by a household's own characteristic evacuation tendency, but also by the evacuation behavior of linked households in its social contact network. It is expected that a household would decide to evacuate if most of its social links have evacuated, due to peer pressure associated with social contagion (Widener et al., 2013; Hasan & Ukkusuri, 2011). For example, once household *a* observes the evacuation of household *b*, household *a* may decide to evacuate as well. The evacuation of both household *a* and *b* (indicated by red shading) may further motivate household *c* and *d* to evacuate. In such a way, evacuation behavior diffuses from one household to another through the social network.

Fig. 3 illustrates how the social network is conceptualized as a home-workplace social network, which has been demonstrated as an improvement upon residential-based networks alone for modeling contagion (Bian et al., 2012). In this study, social links to both residential neighbors and workplace colleagues are assumed to be sufficient to influence a household's decision on hurricane evacuation. The assumption that co-workers are part of social networks that influence household evacuation behavior is based upon findings from two lines of research. First, previous research has found that friendship plays an important role in evacuation behavior (Hasan & Ukkusuri, 2011; Messias, Barrington, & Lacy, 2012). Second, many friendships are formed among workplace colleagues (De Souza Briggs, 2007; Due, Holstein, Lund, Modvig, & Avlund, 1999). Moreover, this assumption has also been applied in other models simulating evacuation behavior (Lindell, 2008; Murray-Tuite, Schweitzer, & Morrison, 2012).

As illustrated in Fig. 3, two households can be socially linked in the model under either of two conditions: 1) both households reside in the same neighborhood (such as a Census block group); or 2) at least one member from each household works at a common workplace, i.e., colleague relationship. The resulting network follows a basic small-world structure (Watts & Strogatz, 1998), where most of social links are highly localized around households, but a few links can reach distant households due to working at same place. Further, since where people live and work can be estimated from Census data, the home-workplace social network may be considered more plausible than an abstract network.

3. Model implementation

3.1. Synthesis of households and workplaces

A synthetic population was created to initialize the simulation

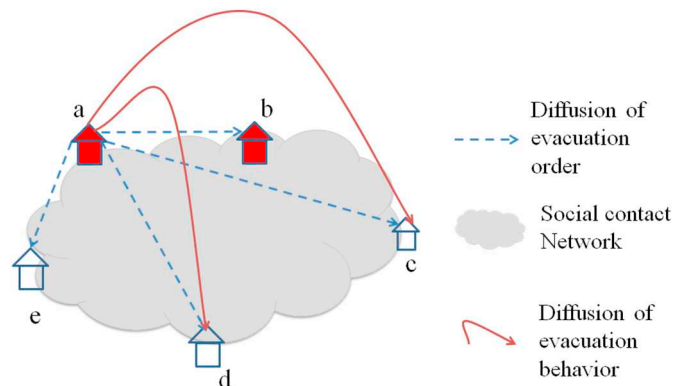


Fig. 2. Illustration of diffusion of evacuation order and evacuation behavior through a social network of households.

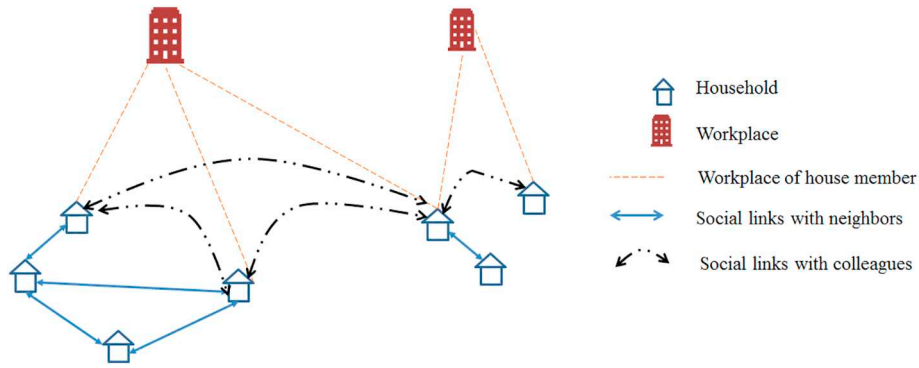


Fig. 3. Illustration of home-workplace social network. Households are connected due to either living in the same neighborhood or having members at the same workplace.

model in concordance with empirical data for the Florida Keys. Specifically, a population of 79,547 individuals was synthesized in the study area and grouped into 35,064 households, according to U.S. Census block group data from 2000 (Census Bureau, 2000). Two sets of information were extracted from the Census data: individual-level data and household-level data (Table 1). Using algorithms developed by Mao and Bian (2010), table cross-referencing and Monte-Carlo simulation were performed to assign attribute values to individuals and households for each Census block group, so that the synthesized distributions fit real demographic distributions. Then, synthetic individuals were filled into a synthetic household based on its household type, size, and number of children and disabilities. To further allocate synthetic households to spatial location, i.e., (x, y) coordinates, residential land parcel data were obtained from the Florida Geographic Data Library and then synthetic households were randomly assigned to those parcels of the same Census block group and same household type. A residential parcel could contain more than one household.

Individuals were assigned to workplaces based on their household location (as origins) and estimated travel distance to work (travel time $\times$ speed of travel mode in Census data). Workplace destinations were determined from a set of 6459 business locations in the study area, including schools, that were obtained from a commercial database (ReferenceUSA, 2003). Each worker was assigned to a business location in which: 1) the industrial code matched that of the worker's occupation; 2) the distance by road to the worker's household matched the estimated travel distance to work from Census data; 3) the maximum number of employees for the business was not yet reached. Unlike workers, school-aged individuals in each household were assigned to a nearest school as their workplace. These algorithms for synthesizing households and workplaces were previously validated by Mao and Bian (2010) using the Census Transportation Planning Products (CTPP) data. Because the synthesized population has the same statistical distribution as the actual population, it is considered broadly representative of the empirically observed reality. Therefore, while the synthetic population necessarily differs from the actual population, its correspondence with empirical data provides a plausible basis for the simulation experiments

conducted with the model.

3.2. Construction of home-workplace social network among households

Each synthetic household was assigned a total number of social links n drawn from a Poisson distribution with a parameter λ that indicates the average number of links in the network. Among the n links, a uniformly distributed random integer number k was then generated between 0 and n to determine how many workplace colleagues would be linked to the household. To do so, k colleagues of household members were selected at random from their synthetic workplaces. Each household was then linked to the households of those k colleagues. The rest of $n-k$ social links were randomly wired to other households in the same block group as their residential neighbors. These procedures were repeated for every household, which completed a home-workplace social network of the study area. This empirically based method of social network simulation is distinct from the abstract networks simulated in other social network ABMs of evacuation (Hasan & Ukkusuri, 2011; Madiredy et al., 2015; Widener et al., 2013).

3.3. Diffusion of evacuation order

Because hurricane evacuation warnings are generally given at least a day in advance of its expected landfall, the model was simulated for a 24-h period using an hourly time step. In the baseline case, the evacuation order is issued at the beginning of the simulation.

In the model, the evacuation order diffuses through two channels: the mass media and the social network among households. Once an evacuation order is issued by authorities, it is broadcast through mass media, such as television, radio and newspaper, and delivered to a given household at a certain probability, named media coverage rate. The baseline media coverage rate was set at 1.1% in the model, indicating that a given broadcast would be expected to reach 1.1% of households per hour. Although this value represents a theoretical rather than empirical assumption, it was determined to be both a plausible and conservative estimate after conducting sensitivity analysis using a range of media coverage rates and broadcast frequencies (Yang, 2013).

If a household was informed about the evacuation order, it would discuss with other households in its social network with a probability referred to as discussion rate d . Through discussion, households unaware of evacuation order were informed and then would discuss with their social contacts, leading to a cascaded diffusion of the evacuation order through the social network. The initial discussion rate $d(0)$ is set to 80% when a household first receives the message and diminishes with the passage of time, as formulated in Eq. 1 (Deffuant, Huet, & Amblard, 2005, p. 1052):

$$d(t) = \begin{cases} d(0) - \gamma t, & \text{if } d(0) - \gamma t > 0 \\ 0, & \text{if } d(0) - \gamma t \leq 0 \end{cases} \quad (1)$$

Table 1

Attributes of synthesized individuals and households from Census and land parcel data.

Individual	Household
Gender	Census block group
Age group	House type
Working status (worker, student, or retired)	Number of household members
Employer type (Industrial code)	Number of children
Disability status	Number of disabilities
Transportation mode to workplace	Vehicle ownership
Transportation time to workplace	Spatial location (x, y)

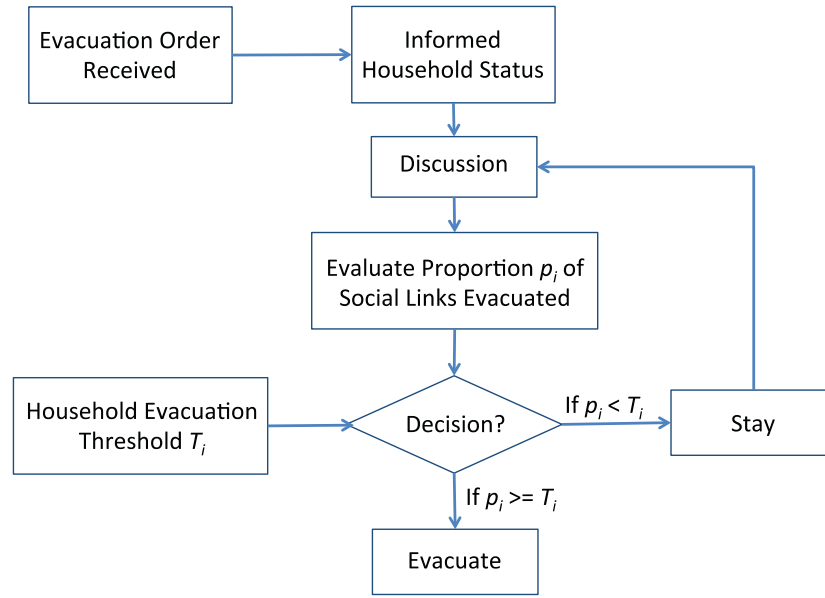


Fig. 4. Flowchart of household decision process toward evacuation.

where t indicates a certain time step. γ is a coefficient affecting the diminishing of discussion with time and was set to 0.017 (Deffuant et al., 2005).

3.4. Diffusion of evacuation behavior

In this study, the diffusion of evacuation behavior among households was modeled with a classic threshold model (Granovetter, 1978), which has also been applied in other hurricane evacuation models (Hasan & Ukkusuri, 2011; Widener et al., 2013). Using the threshold model, a household would decide to evacuate if it learns that at least a threshold fraction of links in its social network are evacuating. Support for this heuristic can be found in the empirical correlation between the decision to evacuate and the influence of peers (Lindell et al., 2005). As illustrated in Fig. 4, once a household i receives the evacuation order, either from the mass media or their social network, this household is considered informed. Following a discussion with their social links, informed household i will evaluate the proportion p_i of social links that have already evacuated or decided to do so. If p_i is higher than their evacuation threshold T_i , the household i would decide to evacuate; otherwise, household i would stay and continue the discussion and evaluation in the next time step.

The value of threshold T_i can vary from 0 to 100% over households due to different risk perception and household characteristics (Hasan & Ukkusuri, 2011). Different households have different thresholds, which are assigned on the basis of empirical evacuation surveys as described in the following section.

3.5. Model calibration

Surveys conducted after major hurricane events were used to estimate households' evacuation thresholds as part of a model calibration process. First, a logistic regression was run on the basis of survey data collected by Irwin and Hurlbert (1995) to identify household characteristics contributing to evacuation from Hurricane Andrew in 1992.² The dependent variable for this logistic regression model indicated whether each of 466 households in southwestern

Louisiana evacuated from Hurricane Andrew, following the analysis by Wilmot and Mei (2004). Independent variables included household type (mobile home, single family house, multi-family building, and others), ownership (owned or rented), size of household members, marital status, age, race, gender of householder, and presence of children. In addition, a binary independent variable was included to indicate whether a mandatory evacuation order was issued or not. The significant results from this logistic regression model are shown in Table 2, with a corresponding R^2 of 35%. For example, as a reflection of the vulnerability context associated with a household's risk perception, living in a mobile home has a significant and strong positive effect on the likelihood of evacuation. In contrast, less vulnerable households living in a single family home were less likely to evacuate.

Second, the results of this logistic regression model were applied to estimate the evacuation tendency of every household in the Florida Keys as a value ranging from 0 to 100%, as presented in Table 3. Overall, the model predicted a 53% evacuation rate of households in the Florida Keys, which is consistent with the observed rate during Hurricane Georges (Dash, 2002; Dash & Morrow, 2001).

Based on the predicted evacuation tendency from this regression model, each household in the agent-based model was assigned an evacuation threshold, assuming that households with lower tendency to evacuation would have higher thresholds. The distribution of evacuation threshold assignments for the Florida Keys presented in Table 3 was estimated using the regression model with Census data for the Florida Keys. The estimated proportions were partially validated with results of evacuation surveys for Hurricane Isabel (Horney, 2009) and Hurricane Georges (Dash, 2002). On one hand, the survey of 2003 Hurricane Isabel indicated 12.5% of residents in the affected area of North Carolina chose to evacuate even though none of their neighbors did (Horney, 2009). To approximate this observed rate, households with the highest evacuation tendency (> 0.9) were assigned a threshold value of zero; these accounted for 15.2% of households in the Florida Keys study area. On the other hand, the survey of Hurricane Georges showed about 35% of respondents would "only consider what is best for them no matter what authorities say" (Dash, 2002), and those households were reluctant to evacuate. To approximate this rate, households with an extremely low evacuation tendency (< 0.4) were either designated as stayers or assigned extremely high thresholds (0.8 and 1.0). As indicated in

² We thank Drs. Irwin and Hurlbert for sharing their survey data on evacuation from Hurricane Andrew for use in this study. Details about the data are provided in the report by Irwin and Hurlbert (1995).

Table 2
Household characteristics that significantly* contribute to evacuation tendency.

Variable	Coefficient	Significance
Intercept	−0.8000	0.0769
Living in a mobile home	2.3613	0.0002
Living in a single-family house	−0.8580	0.0474
Evacuation order given	1.2346	< 0.0001
Presence of children	0.6186	0.0127
Female householder	0.3424	0.0029
Senior householder (Age > 65)	−0.9791	0.0369

* Statistical significance is shown for variables with $p < 0.05$.

Table 3
Assignment of household evacuation thresholds based on evacuation tendency.

Evacuation tendency	Evacuation threshold T_i	% of households ^a	Supporting source
0–0.37	Stayer (decline to evacuate)	12.5	Dash (2002)
0.37–0.38	1	10.9	
0.38–0.4	0.8	12.3	
0.4–0.5	0.5	9.9	Equal interval assignment
0.5–0.6	0.4	8.3	
0.6–0.7	0.3	21.6	
0.7–0.8	0.2	4.1	
0.8–0.9	0.1	5.3	
0.9–1	0	15.2	Horney (2009)

^a The percentage of households assigned to each category was estimated from the logistic regression model indicated in Table 2 on the basis of Census data for the Florida Keys.

Table 3, these three categories accounted for a total of 35.2% of households in the study area. Thresholds for the rest of the households were assigned using an equal interval method.

4. Results and discussion

4.1. Social influence on temporal diffusion of evacuation behavior

To assess the effects of social influence on evacuation behavior, a sensitivity analysis was undertaken for the model in which the average number of links λ per household was varied from 2 to 8 with an increment of 1 to construct different network scenarios, as shown in Fig. 5. This range was chosen based on statistical results from the General Social Survey (Davis, Smith, & Marsden, 2005), and to be consistent with the assumption that given the limited time and emergency situation, households would only contact those trustworthy friends and neighbors who are closely connected to them. Since only a small number of trusted contacts would be consulted by each household, limiting the most connected of these network structures to 8 average contacts may be considered as allowing a generous upper bound.

Fig. 5 shows the simulated number of households evacuating each hour under these different network structures (λ from 2 to 8). For each social network structure, an evacuation curve was plotted to depict temporal patterns of evacuation behavior in terms of the number of new households evacuating over a 24-h period. Each evacuation curve depicted in Fig. 5 represents an average across 50 model realizations for each social network structure so as to reduce the effect of stochastic variation on the overall evacuation trend. These results show that when households have more social links, evacuation behavior diffuses faster with a higher peak and earlier peak time. For example, diffusion in the social network with an average of 8 links peaked 4 h earlier than the social network with an average of 2 links. The corresponding peak size was almost doubled from 1800 to 3500 households. This pattern arises because more social links facilitate the spread of the evacuation order,

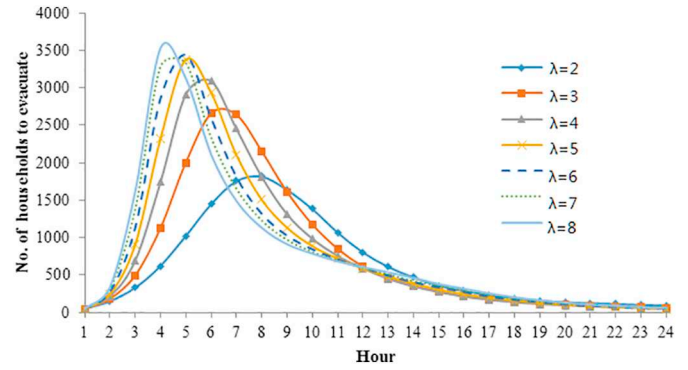


Fig. 5. Diffusion of evacuation behavior over time under different social networks (λ from 2 to 8 average links).

triggering more rapid social contagion of evacuation behavior.

The overall evacuation rate, derived from the area under the curves shown in Fig. 5, also improved as the average number of social links increased. The overall evacuation rate ranged from 43.6% to 54.5% under different social networks. The network structure with an average of 4 social links produced an evacuation rate of 53.2% (95% CI: [52.6, 54.3]) was the closest to the observed evacuation rate of 53% from the survey (Dash, 2002). Thus, this social network was selected to further explore the spatial dynamics of evacuation behavior and simulate evacuation traffic for evaluation.

4.2. Spatial-temporal patterns of evacuation behavior

To illustrate the spatial spread of evacuation, a series of maps was created to display evacuation intensity over time and location, as shown in Figs. 6 and 7. The evacuation intensity was estimated with a kernel density function as the number of newly households to evacuate during a 4-h interval in a 50 m cell location. The cell size was set to approximate the average size of land use parcels. All results were averaged from 50 model realizations to reduce the effect of stochastic variation on the results of each simulation run.

The map in Fig. 6 presents the evacuation intensity in the most populous area, the city of Key West. A full view of entire Florida Keys is shown in Fig. 7. Evacuation intensity was classified into 5 categories: extremely low (0–50 households per km^2), low (50–200), moderate (200–500), high (500–1000), extremely high (> 1000). After the evacuation order was issued at Hour 1, the evacuation behavior was at a low to moderate level for the first 4 h (Fig. 6a). The evacuation intensity was under 50 households per km^2 for most areas in the city. There were only three small spots with high evacuation intensity (> 500), all of which were in the central and eastern part of Key West. These hot spots emerged in areas with high household density and households that had a very low evacuation threshold.

As time proceeded, the evacuation peaked between Hour 5 and 8 (Fig. 6b). Evacuation intensity was above 200 households per km^2 in most areas, and the maximum evacuation intensity exceeded 3000 in the central Key West. As more households decided to evacuate, they imposed increasing peer pressure to their social contacts and motivated them to follow the same behavior. During the third 4-h period (Fig. 6c), the intensity of evacuation dropped quickly to a low level (50–200 households per km^2). The most active areas moved from the central city to the western side of the city, where the intensity remained at a moderate level. This map suggested that after 8 h there were still many households left in the western city having not yet decided to evacuate. Fig. 6d–f shows that evacuation intensity gradually receded during the last 12 h of simulation, due to three reasons: 1) the pool of households to evacuate was depleting; 2) the discussion rate between households was approaching zero; 3) households leftover had extremely high thresholds and strong will to stay rather than evacuate.

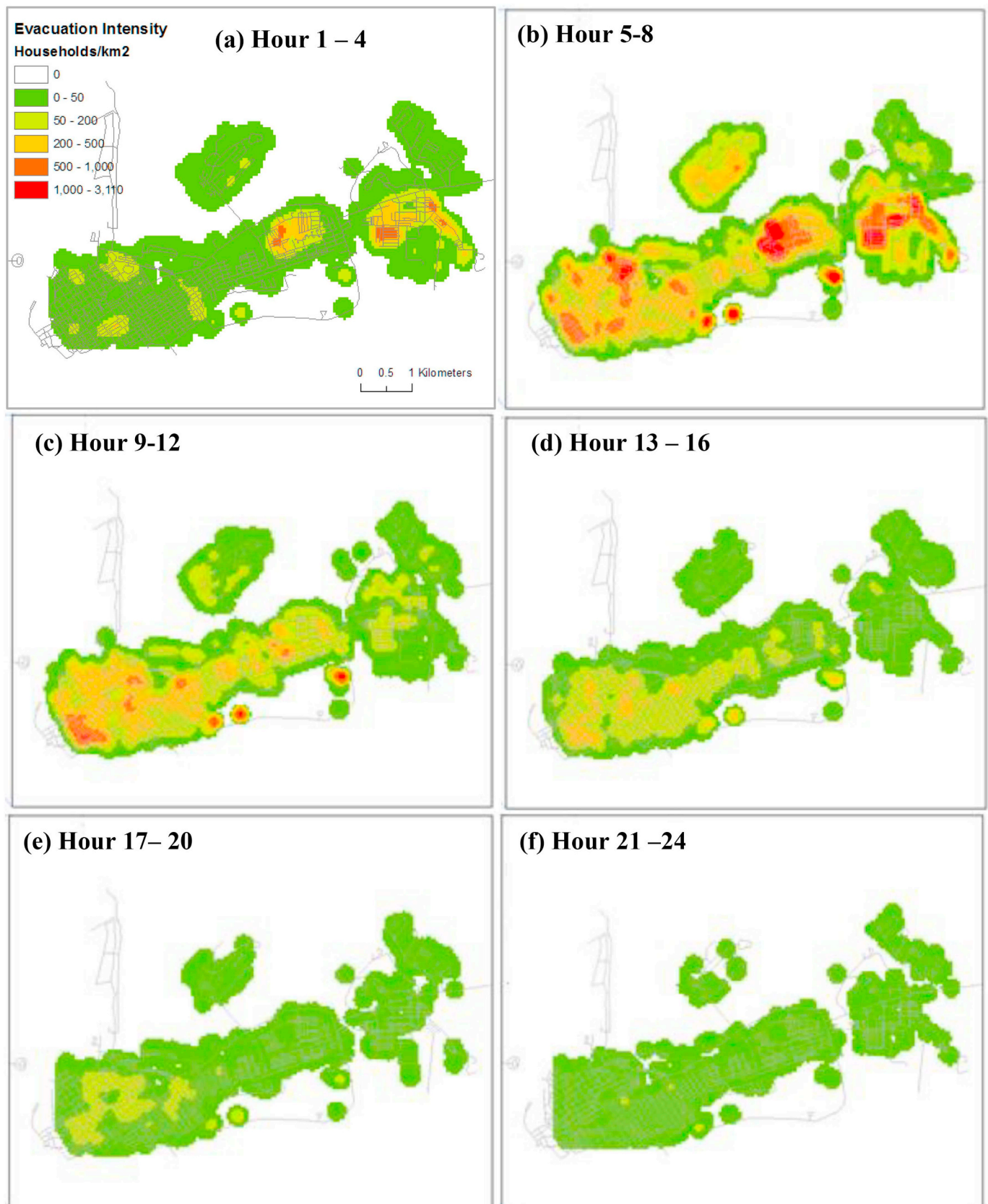


Fig. 6. Evacuation intensity in the city of Key West at 4-h intervals under the social network ($\lambda = 4$). The intensity of evacuation (in households per km²) was classified into 5 categories: extremely low (0–50), low (50–200), moderate (200–500), high (500–1000), extremely high (> 1000).

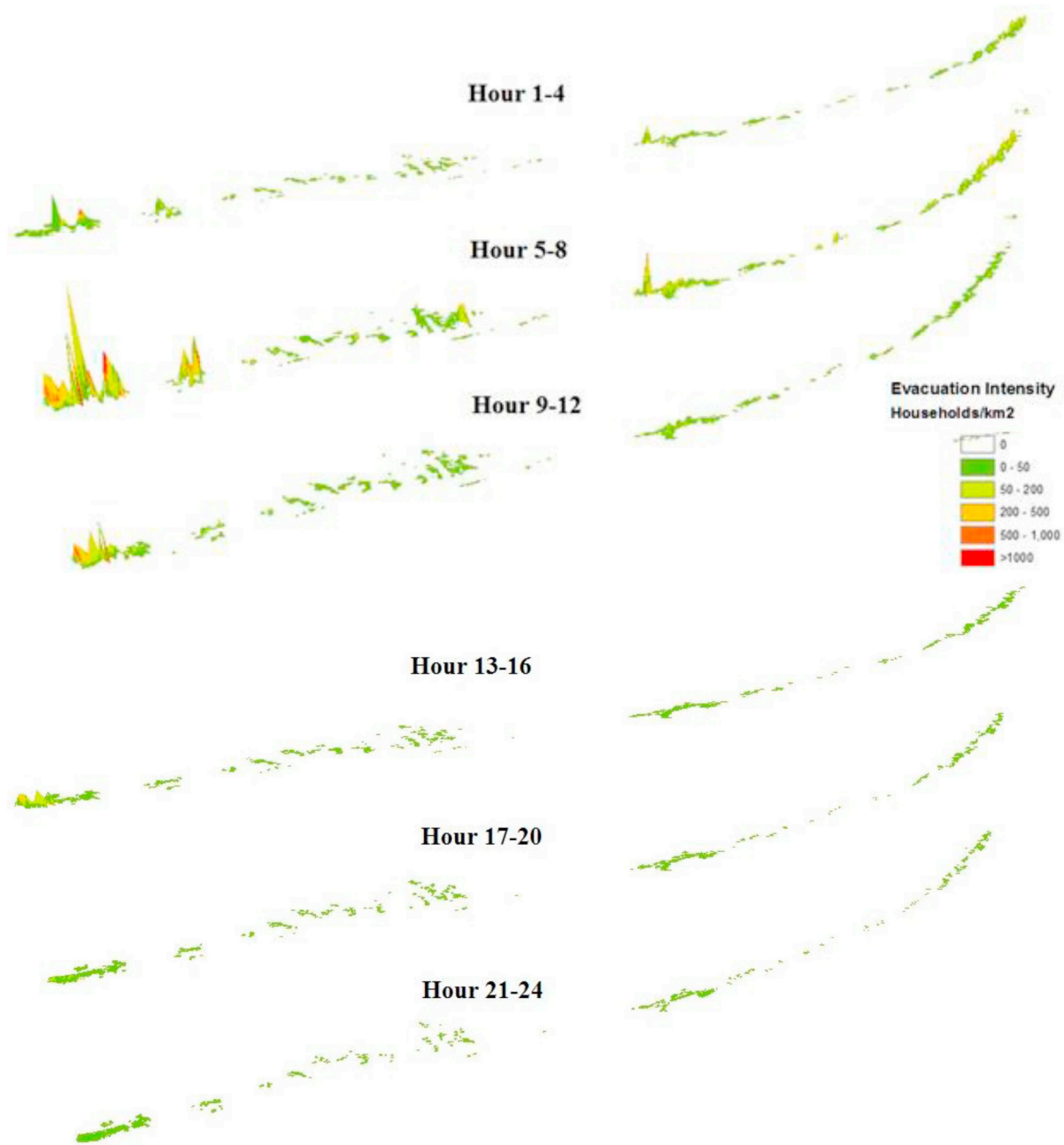


Fig. 7. 3D view of spatial distribution of households with evacuation decision over a day at 4-h intervals under the social network ($\lambda = 4$). The intensity of evacuation (in households per km^2) at a given cell is classified into 5 categories: extremely low (0–50), low (50–200), moderate (200–500), high (500–1000), extremely high (> 1000); each cell is extruding to a height proportional to its evacuation intensity.

Fig. 7 maps hurricane evacuation intensity over time for the entire Florida Keys. Beyond the city of Key West, the urban areas of Marathon (in the Middle Keys) and Key Largo (in the Upper Keys) had clusters of moderate evacuation intensity in the first 4 h, while the rest of areas were at a low level. From hour 5 to 8, those clusters expanded throughout the entire Florida Keys. The maximum intensity at Marathon was about half of that at the central Key West. In the period of hour 9–12, the areas with moderate evacuation intensity shrunk dramatically in the Marathon and Key Largo areas. For the last 12 h, the intensity of evacuation dropped back to the low level for the entire study area.

Spatio-temporal patterns shown in Figs. 6 and 7 shed insights into evacuation management for local authorities; for instance, the allocation of traffic control efforts. The number of households to evacuate increases exponentially after hour 3, and reaches a peak about 6 h after

the evacuation order is issued, indicating that local authorities have such amount of time to distribute traffic control personnel. The city of Key West should be given priority in evacuation, not only because of its highest intensity of evacuation, but also the farthest distance to the mainland. For evacuating this city's population, the traffic control efforts should be first allocated to the eastern side in hour 1–9, and then gradually move to the western side from hour 10 to 16. In addition to Key West, another area in need of attention is the urban area of Marathon (in the Middle Keys). This area has high traffic demands from evacuation that are synchronous to Key West and encountered midway along the evacuation route for people from Key West. An ability to maintain the flow of traffic in Marathon thus determines the overall efficiency of evacuation for the entire Florida Keys.

4.3. Model validation

As an imitation of the real, a simulation model will never be valid in an absolute sense. Nonetheless, model validation is an important kind of model analysis, given that a model's utility arises in part from the authenticity with which it mimics that reality. Here, the model validation process involves a comparison of simulated and empirically observed evacuation traffic over time. Different data were used for validation than for calibration of the evacuation threshold assignments. Efforts to validate the model were undertaken using empirical traffic data for evacuation from Hurricane Georges in the Florida Keys. In this process, the simulated spatial-temporal dynamics of household evacuation behavior were first input into the TRANSIMS (TRansportation ANalysis SIMulation System) software package (Barrett et al., 2001). The simulated traffic pattern was then compared to empirical observations of evacuation traffic recorded at a traffic monitoring station during the evacuation from Hurricane Georges (FDOT, 2012). Evacuation of residents from the Florida Keys occurred primarily over one day (FDOT, 2012), in line with the 24-h time horizon used for simulation.

Three evacuation orders were issued on September 23, 1998 for different parts of the Florida Keys. The orders were given during daytime hours in part because most households prefer diurnal travel. The first evacuation order was issued between 6:00 and 7:00 am for the Lower Keys; the second evacuation order was issued at 11:00 am for the Middle Keys; and the third evacuation order was issued at 4:00 pm for the Upper Keys (Dash & Morrow, 2001). These evacuation orders were input into the model for the affected areas, and the resulting simulated hourly traffic was compared to the recorded traffic at the entrance to the mainland (Fig. 8). In general, the simulation results align with the observed traffic in terms of both timeline and magnitude. After the evacuation order was issued, the traffic rose fast after some delay caused by discussion or packing. The simulated evacuation traffic peaked at 1:00 pm, approximately the same time as the recorded traffic peaks. The peak size of simulated traffic was also similar to that of the recorded traffic volume, within a range of 1500–1700 vehicles per hour. The simulated peak was close to the designed capacity, 1600 vehicles per hour, of a two-lane road. These results indicate that traffic congestion might occur on the two-lane part of the Florida Keys road network. From this comparison of recorded and simulated traffic patterns during evacuation, the reasonableness of the model is established as a platform for predicting evacuation traffic and supporting policy design.

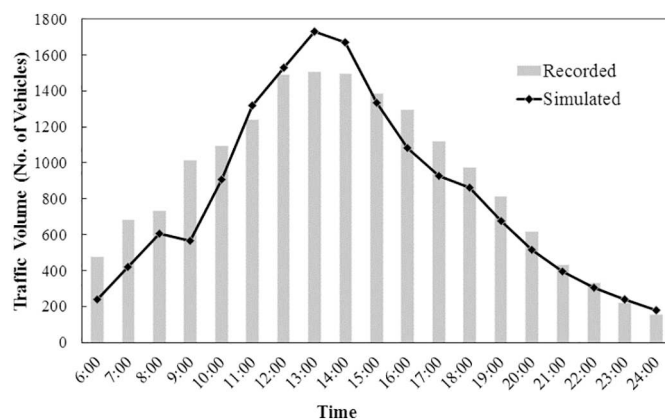


Fig. 8. Simulated and recorded hourly traffic volume on Sept. 23, 1998. The Y axis represents the traffic volume per hour; X axis represents the 24 h of a day. Hour 1 represents the hour between 6:00–7:00.

4.4. Model extensions

Having established a correspondence between the simulated and observed evacuation patterns for the case of Hurricane Georges, the model was used as a virtual platform for further experimentation with alternative warning strategies and transportation planning to inform local evacuation policy during future hurricane events (Yang, 2013). Simulation of door-to-door notices, for example, produced greater evacuation rates in the model than could be achieved from a single order issued as a mass media broadcast. Inclusion of the bus as a public transit option was also tested and demonstrated an increased evacuation rate. These experiments show that encouraging residents and tourists to evacuate by bus not only alleviates congestion but also ensures that those who lack access to private cars can evacuate safely.

While these model extensions are particularly relevant to the study area of the Florida Keys, the model itself may be adapted to other coastal areas that are vulnerable to hurricanes. Insights from such adaptation to other geographic contexts would reveal relative effects of more complex transport networks and different population characteristics on simulated evacuation behavior. Using empirical data to ground the development of a locally relevant simulation model facilitates the exploration of alternative scenarios and identification of effective plans for future evacuation needs. Furthermore, the approach presented herein may also be extended to model evacuation from areas impacted by other natural disasters.

4.5. Model limitations

Although any model is inherently a simplification of reality, there are at least two limitations of this study that could be addressed in future research. First, this research drew upon survey data from Hurricane Andrew to parameterize evacuation thresholds for the model due to the lack of comparable surveys conducted in the Florida Keys after Hurricane Georges. While the survey of Hurricane Andrew in southwestern Louisiana provided a reasonable proxy due to the demographic characteristics of the affected population, such calibration would be improved if similarly detailed survey data were available for the Florida Keys.

Second, the island-chain of the Florida Keys extends more than one hundred miles. When a hurricane hits this area, its impact varies in different parts of the Keys, and so do the risks perceived by residents. It is likely that residents in the area where the hurricane will land would perceive much higher risks than those who live far away from the landfall. This research assumed that all residents, no matter where they reside, perceived the same level of risk toward an incoming hurricane, and overlooked the spatial heterogeneity of risk among residents. Extensions of this research include consideration of alternative scenarios for the location of a hurricane landing, whether in the Lower, Middle, or Upper Keys areas. For these location-specific landing scenarios, the distance between the residence and the location of hurricane landfall could be used to estimate the level of perceived risk that is incorporated into the model of household decision toward evacuation.

5. Conclusions

This study enriches the research on hurricane evacuation by integrating a home-workplace social network into an agent-based simulation model so as to experiment with social influence on household evacuation behavior. The spatial diffusion process of evacuation behavior was emphasized and explicitly represented for the geographical context of the Florida Keys. The model was empirically grounded in several ways: construction of the social network incorporated information about residential and workplace locations; household evacuation thresholds were estimated using data from hurricane evacuation surveys; and resulting traffic patterns were validated with observations from traffic records. The model enables iterative

exploration of how the evacuation process may proceed to encourage appropriate questions and alternative assumptions. The results generated from experiments with this model provide valuable insight for designing future hurricane evacuation plans in the Florida Keys. More broadly, the approach taken in this study may be extended to other areas affected by hurricanes and other natural disasters.

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